Journal of Agricultural and Resource Economics 47(1):209–224 ISSN: 1068-5502 (Print); 2327-8285 (Online)

doi: 10.22004/ag.econ.310527

Market Responses to Export Restrictions from Highly Pathogenic Avian Influenza Outbreaks

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Export restrictions often exacerbate the direct production losses and control costs from infectious animal disease outbreaks by reducing the pool of consumers of animal products. However, the uncertain timing and the varying extent of the trade restrictions make it challenging to measure these indirect costs of disease outbreaks. We examine two outbreaks of highly pathogenic avian influenza (2004 and 2014–2015) that saw few broiler chickens lost but significant trade disruptions from embargoes. We evaluate the timing and estimate the magnitude of the economic shocks from these embargoes, finding brief but considerable trade declines and distinct economic responses to each outbreak.

Key words: event study, HPAI, infectious animal disease, international trade policy

Introduction

Two outbreaks of highly pathogenic avian influenza (HPAI)—a highly contagious and deadly disease of poultry—disrupted the U.S. broiler (chicken) meat market in 2004 and 2015. While the production losses from HPAI infections and disease control were small for the broiler industry during both outbreaks, embargoes and other trade restrictions on U.S. broiler meat substantially decreased exports (Johnson et al., 2015; Ramos, Maclachlan, and Melton, 2017). Limited information on the timing of the restrictions imposed by different foreign importers was made public, hindering the identification of the magnitude of trade impacts and market responses. Accurate estimates of the economic impacts of HPAI help federal agencies improve public disease monitoring and mitigation efforts (Greene, 2015).

In this article, we estimate the effects of the two outbreaks of HPAI and the ensuing embargoes on the U.S. broiler meat market. Our inability to directly observe how trade restrictions affect broiler meat markets introduces considerable uncertainty into any empirical approach (i.e., specification uncertainty). We address this uncertainty using publicly available information on these disease outbreaks and optimal model selection. Using these approaches, we find sizable export declines and changes in prices and storage during and after HPAI outbreaks. Our estimated changes in producer welfare differ substantially from those found in related studies.

During many livestock disease outbreaks, including HPAI, the World Organisation for Animal Health (OIE) recommends reducing the trade of live animals and animal products to lower the risk

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We thank Kamina Johnson and Amy Delgado for providing comments and Christina Letsou for reviewing the empirical methods. The findings and conclusions in this publication are those of the authors and should not be construed to represent any official USDA or U.S. Government determination or policy.

Review coordinated by Dragan Miljkovic.

of disease spread.[1] These trade restrictions and resulting market responses extend economic losses beyond the producers directly affected by HPAI outbreaks. Ramos, Maclachlan, and Melton (2017) observe that year-over-year revenue declined around $4 billion for broiler meat producers between 2014 and 2015, indicating substantial economic losses. The distinct timing of the embargoes and varying types of restrictions imposed by different countries and foreign importers during and after HPAI outbreaks complicates the measurement of market responses (Johnson et al., 2015; Thompson, 2018).

To estimate the economic impacts of HPAI on the broiler industry in 2004 and 2015, we combine a time series of U.S. broiler meat market variables with feed prices, industrial energy prices, and other macroeconomic variables. In addition to imposing structural breaks based on available information on the outbreaks, we apply a model selection approach that determines the timing of outbreak responses and is similar, in principle, to the methods described by Bai and Perron (2003).[2] Our specifications follow the time-series techniques initiated by Sims (1980). Vector autoregressive (VAR) models account for the endogenous and autocorrelated relationships among broiler meat market variables and accommodate time trends and exogenous variables. The uncertain timing of the response to HPAI complicates the translation of well-developed methods used to evaluate shocks to similar markets (e.g., Hamilton, 2003; Kilian, 2008). In contrast to a single, easily defined event, the periods when trade restrictions affected broiler meat markets are ambiguous because the intensity of these restrictions changed gradually over time and varied across countries (Johnson et al., 2015). We implement an event study approach and test a wide range of outbreak response window (ORW) durations—along with other specification choices—and evaluate models based on their estimated information loss.

Changes in production, consumer preferences, and international trade policy also raise the possibility of different economic responses to outbreaks of the same disease over time. Increased production intensification and global connectivity alter the risks posed by—and the responses to—infectious disease outbreaks (Perrings et al., 2005; MacDonald and McBride, 2009). Macroeconomic conditions and consumer preferences also changed during this period. We therefore use our approach to test whether disease outbreaks should be modeled as similar events.

We expand the literature on the economic impacts of livestock diseases by estimating the effects of embargoes from infectious disease outbreaks. Our results identify declines in exports and prices and increases in the cold storage of broiler meat. These changes occur at or near the end of the disease outbreaks and persist for several months afterward.

This article presents an empirical estimation of the economic impacts of embargoes and other trade restrictions following animal disease outbreaks. The estimates derived from this approach could also motivate the imposed economic shifts in epidemiologic–economic models.[3] Our empirical study requires few assumptions and uses data aggregated over product types to capture industry-wide changes, creating a compelling metric of welfare loss. It also extends economic research on behavioral responses to human or zoonotic disease outbreaks and subsequent centralized control efforts (e.g., Towers and Chowell, 2012; Springborn et al., 2015) into market responses to animal diseases. It contributes an empirical application to a growing body of literature on the econometric identification of the relationship between agricultural policy and markets (e.g., Carter and Smith, 2007; Carter, Rausser, and Smith, 2017; Janzen, Smith, and Carter, 2018).

[1] The potential for zoonosis (transmission from animals to humans) can further diminish demand and motivate stricter restrictions among foreign importers during infectious animal disease outbreaks (Sumner, Bervejillo, and Jarvis, 2006). There was little to no evidence of consumer avoidance responses, domestically.

[2] Both studies determine the timing of structural breaks by minimizing the sum of squared errors. Bai and Perron construct confidence intervals, while we characterize specification uncertainty using suboptimal models.

[3] Animal disease economists often depend on spatial, stochastic models of disease spread such as the North American Animal Disease Spread Model (NAADSM) or the InterSpread Plus model, combined with partial equilibrium models like the Paarlberg model and computable general equilibrium models to simulate the epidemiology and economics of disease outbreaks (U.S. Department of Agriculture, 2013; Johansson, Preston, and Seitzinger, 2016). These simulation models, however, do not directly estimate economic changes from observed outbreaks.

International Trade Policy Response

Avian influenza viruses spread quickly among poultry and wild birds directly or through contaminated environments. World Organisation for Animal Health (2021) defines highly pathogenic avian influenza strains as those that cause mortality in 75% or more of poultry birds. To reduce the risk of disease spread, the United States imposes movement restrictions and other countermeasures inside control areas and *immediately* notifies the international community.

Some importers impose embargoes on U.S. broiler meat after verifying HPAI among U.S. poultry or other hosts such as wildlife or companion animals. The World Trade Organization supports these trade barriers under the Agreement of Sanitary and Phytosanitary (SPS) Measures of 1998 as a means of protecting the health of people and animals in the importing nation (World Trade Organization, 1998). Regional trade groups and sovereign nations select their trade policies on a case-by-case basis, and individual companies can also decline purchases from high-risk areas. Diseases that appear on the OIE's former Notifiable Disease List A typically trigger severe import restrictions or embargoes.[4]

We focus on two notable outbreaks of HPAI in the United States as case studies. In 2004, a single, small (6,600 head) broiler production facility and two live-bird markets in Texas had confirmed cases of HPAI (Pelzel, McCluskey, and Scott, 2006).[5] The disease was detected soon after its introduction, and the response implemented by the Texas Animal Health Commission and the Animal and Plant Health Inspection Service (APHIS) quickly stifled disease spread, preventing direct losses of nearby poultry producers.[6] However, the outbreak led 44 importers to impose embargoes on poultry and poultry products from Texas or the entire United States (Pelzel, McCluskey, and Scott, 2006).

In the months before the U.S. outbreak in 2004, outbreaks of HPAI also began in the Republic of Korea, Thailand, Vietnam, Japan, Hong Kong, Cambodia, Indonesia, and China, which significantly reduced exports of broiler meat from and broiler production in these countries.[7] The World Health Organization (2012) reported transmissions of HPAI from birds to humans (zoonosis) in Thailand and Vietnam, which introduced public health concerns. The outbreaks abroad likely improved the international demand for U.S. poultry products, thus mitigating the loss of export markets following the outbreak in the United States. These competing forces still led to a net reduction in U.S. broiler meat exports (Leuck, Haley, and Harvey, 2004).

The 2014–2015 outbreak progressed quite differently. Migratory waterfowl introduced two strains of HPAI into the United States between December 2014 and June 2015.[8] Two hundred and eleven commercial flocks and 21 backyard flocks were subject to stamping-out, resulting in the loss of over 50 million birds (U.S. Department of Agriculture, 2016). Ramos, Maclachlan, and Melton (2017) note that the vast majority of losses occurred among egg-laying chickens (layers) and turkeys, which reduced their flock sizes by 12% and 8%, respectively. In contrast, broiler chicken inventories fell by less than 0.01%. However, the aggregate revenues of the egg and turkey industries increased while broiler industry revenues fell by 12% in 2015.

Some foreign importers of U.S. broiler meat imposed embargoes following the initial report of the first case of HPAI in January 2015, while others waited until the disease prevalence was at its highest between the end of April and the beginning of June of 2015. The OIE guidelines would suggest lifting embargoes approximately 4 months after the last observed case (June 2015), but

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[4] OIE categorized extremely damaging diseases such as foot and mouth disease and Newcastle disease as List A diseases. List B included diseases that were considered less economically damaging such as avian tuberculosis (World Organisation for Animal Health, 2004). The OIE has since combined these diseases in a single list.

[5] Numerous strains of avian influenza can be highly pathogenic. H5N2 spread during the 2004 outbreak.

[6] Stamping-out, as defined in the OIE Terrestrial Animal Health Code glossary, is the elimination of an outbreak by killing infected and susceptible animals in affected flocks and, where appropriate, flocks exposed through direct or indirect contact; the disposal of carcasses and animal products; and the cleansing and disinfection of facilities (World Organisation for Animal Health, 2021).

[7] A different strain of HPAI, H5N1, caused these outbreaks of HPAI outside of the United States.

[8] H5N8 HPAI infected birds only in Washington, Oregon, and California, while H5N2 HPAI spread across 15 states.

Johnson et al. (2015) note this timing also differed by the trading partner. Differences may be due to country-specific trade policies.

Between the 2004 and 2014–2015 HPAI outbreaks, the OIE adopted guidelines promoting the use of zoning and compartmentalization—or designating areas within a country as "restricted" or "disease-free"—instead of nation-wide embargoes (Scott et al., 2006; World Organisation for Animal Health, 2021). Establishing compartments requires approval before an outbreak and adherence to OIE's policies. Regionalization policies that separate areas within a country based on health status represent a closely related and readily available alternative. While compartments were not designated before the 2014–2015 HPAI outbreak, 38 countries imposed regionalized embargoes in response to this outbreak (Greene, 2015). These regionalized embargoes could encompass small epidemiological zones containing infected flocks, up to groups of states where inflected flocks were found. The absence of HPAI in key broiler producing states in the Southeastern United States allowed for continued exports of broiler meat to countries imposing regionalized embargoes. Eighteen foreign importers, including three major U.S. poultry destination markets—China, South Korea, and Russia—imposed persistent, nation-wide embargoes.[9] Previous simulation studies concluded that regionalization policies could mitigate the effects of embargoes on U.S. producers (Paarlberg, Seitzinger, and Lee, 2007). As a recent example, the United States and the Republic of Korea reached an agreement in 2018 to use regionalization during future HPAI outbreaks (U.S. Department of Agriculture, 2018).

Data and Methods

We build upon recent research on the economic impacts of the 2014–2015 HPAI outbreak that rely on simulations (Johansson, Preston, and Seitzinger, 2016) or year-over-year comparisons (Greene, 2015; Ramos, Maclachlan, and Melton, 2017) by developing and applying an appropriate econometric framework. A time-series approach allows us to more rigorously address some of the complexities identified in these previous studies. We apply an event study framework (similar to the second method used by Carter and Smith, 2007) to assess these persistent market shocks.

Ramos, Maclachlan, and Melton (2017) note a delay between the first case of HPAI and changes in the broiler meat market. They suggest that the rapid increase in cases from hundreds of thousands of birds in late March to tens of millions of birds in April and May contributed to this delay. In contrast to the observed timing and intensity of production losses from HPAI, the timing of embargoes and responses of private firms were ambiguous. To apply an econometric framework to this ambiguously timed market response, we take two approaches. First, we impose a standard event window based on disease prevalence and OIE guidelines. Second, we select the optimal window of broiler meat market responses to HPAI based on how well it fits the data. The first approach benefits from modeling an arguably exogenous shock to the system, while the second approach provides insights into the timing of market shifts. The second approach provides the best model fit at the risk of detecting other shocks.

To address specification uncertainty, we evaluate $N = 111,4448,792$ plausible candidate models. All models include our endogenous broiler meat market measures in a distinct VAR specification, while individual models include different trends, exogenous covariates, lag lengths, and response windows to the HPAI outbreaks. We also consider the inclusion of error correction terms in the online supplement (see www.jareonline.com). Information criterion (IC) values establish the performance of each model by balancing the model fit and parsimony, and the online supplement includes a thorough description.

[9] Russia's import ban preceded the 2014–2015 HPAI outbreak during heightened tension over the annexation of Crimea.

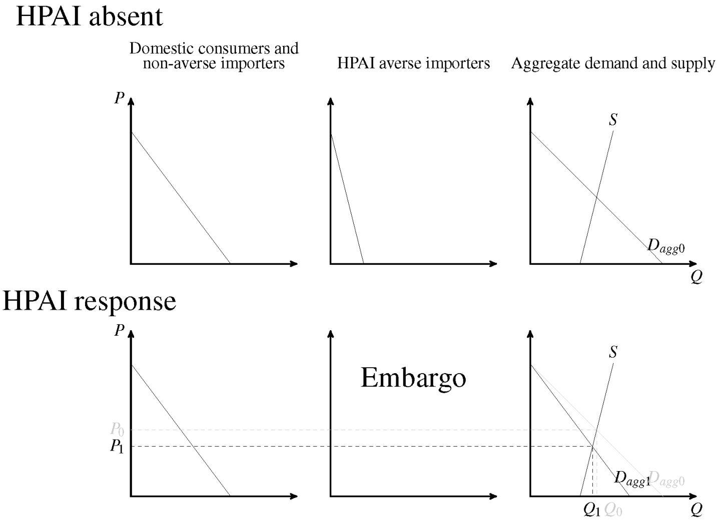

Figure 1. Model of Reduced Aggregate Demand for U.S. Broiler Meat from an HPAI Outbreak

Conceptual Framework

We first present a static, conceptual model of the effect of embargoes on broiler meat markets. This model guides specification choices and welfare analysis. Our focus is on the changes in the U.S. broiler meat market from HPAI related trade restrictions. Changes in broiler meat prices and availability also impacted the welfare of upstream input suppliers and downstream consumers. However, measuring these welfare impacts is beyond the scope of this article.

While domestic consumers and some foreign importers did not respond to the HPAI outbreak, trade restrictions imposed by other foreign importers decrease the aggregate demand for U.S. broiler meat. We present a steeply upward slopping supply curve in our conceptual model and allow for supply responses in our empirical approach, but we typically find little evidence of price responsiveness in the short run. Ramos, Maclachlan, and Melton (2017) report that changes in the production of broiler meat were positive around the 2014–2015 HPAI outbreak. Figure 1 qualitatively captures the expected changes from HPAI in exports, prices, and production. For simplicity, we exclude meat storage; however, storage can be evaluated as part of the supply response in a static model. In the absence of HPAI, consumers from two groups demand U.S. poultry products; embargoes prevent consumption by the HPAI-averse importers. Figure 1 depicts two market equilibria, one in the absence of HPAI and a second following HPAI related trade restrictions. We expect price and quantity declines $(P_1 < P_0; Q_1 \leq Q_0)$ as the pool of consumers shrinks.

A comprehensive estimate of producer welfare changes from HPAI requires the inclusion of revenue and cost estimates. Limited data on producers' costs constrain our welfare analysis to evaluate changes in revenues as a means for approximating producer surplus. Other studies have suggested that broiler producers' costs decreased during the pandemic due to decreasing feed costs, which would indicate that our estimates represent an upper bound of welfare losses (Johansson, Preston, and Seitzinger, 2016). However, all sources of costs are not observed. The minimal observed changes in production and observable input prices imply that most of the change in welfare is due to changes in prices as supply remained approximately fixed.

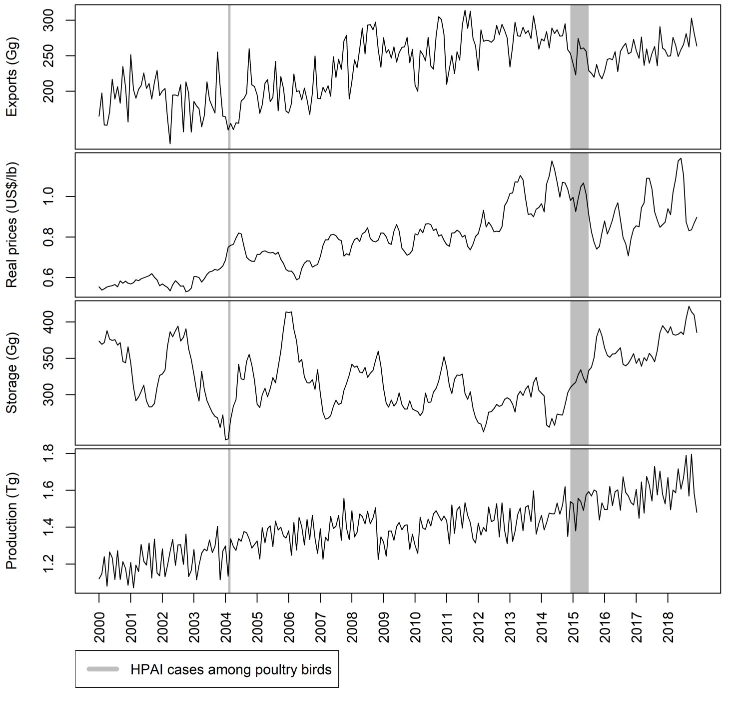

Figure 2. Monthly Export Volume, Average Prices, Storage Volume, and Production Volume of Broiler Meat, 2000–2018

Data

Our data cover the market for U.S. broiler meat and several variables that proxy for the cost of production and domestic and international demand for broiler meat products. Four simultaneously determined economic measures—export volumes, retail prices, storage volumes, and production volumes—indicate each month's market conditions. Industrial energy prices, soybean meal prices, corn prices, domestic per capita disposable income, and global real economic activity are considered exogenous variables and characterize macroeconomic conditions. Natural log transformations of all the variables allow us to interpret coefficient estimates as elasticities or percentage changes in response to the HPAI outbreak.

The econometric model includes variables at monthly intervals between 2000 and 2018. The Foreign Agricultural Service's Global Agricultural Trade System (GATS) provides export data from the U.S. Bureau of the Census (U.S. Department of Agriculture, 2019b); the Economic Research Service (ERS) reports chicken meat prices (U.S. Department of Agriculture, 2019c); and the National Agricultural Statistics Service's (NASS) *Cold Storage Report* (U.S. Department of Agriculture, 2019a) from the Quickstats database reports storage and production data (U.S. Department of Agriculture, 2019d).

Figure 2 shows the level of each market variable from January 2000 to December 2018. The time series include a shaded area representing months when APHIS recorded cases of HPAI in poultry birds in the United States. Note that these shaded regions do not necessarily coincide with the timing of trade restrictions. Visual inspection of the graphs suggests that exports and storage changed near the end or following each outbreak, aligning with Ramos, MacLachlan, and Melton's (2017) observations. Prices increased following the 2004 outbreak and decreased following the 2014–2015 outbreak. The market variables do not substantially deviate from historical ranges during their responses to HPAI.

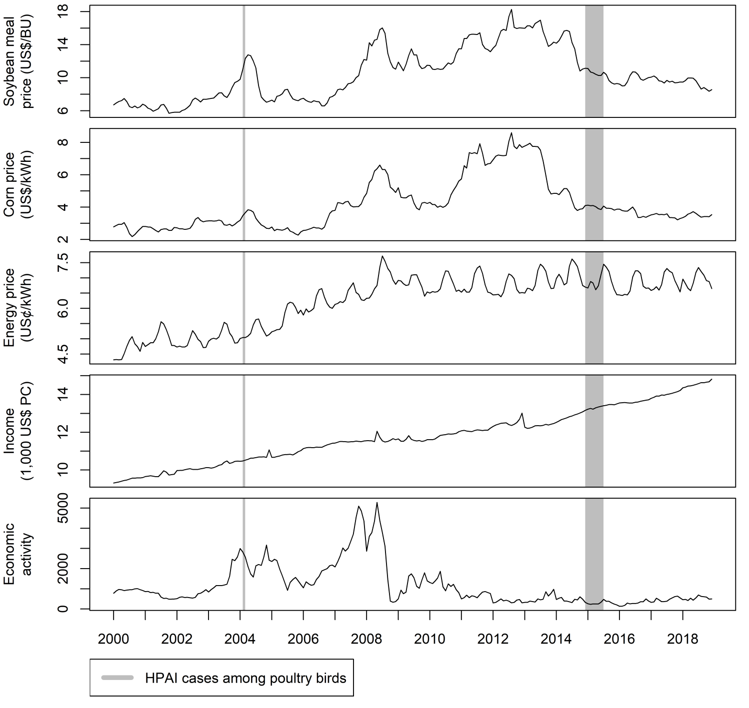

Figure 3. Monthly Industrial Energy Prices, Domestic per Capita Disposable Income, and Global Real Economic Activity, 2000–2018

Forces outside the broiler meat market also drive changes in its supply and demand. The costs of production and storage influence the volume of meat brought to market. The disposable income of consumers—foreign and domestic—influences their willingness to buy meat products. We proxy for production cost changes with industrial energy (a significant input into both production and storage) and feed (soybean meal and corn) prices. Changes in demand are measured using the domestic per capita income and global real economic activity. We use the U.S. Energy Information Administration's (2019) monthly data on industrial energy prices, received prices per bushel as of soybean meal and corn (U.S. Department of Agriculture, 2019a), and Federal Reserve Economic Data (2018) on real, domestic per capita disposable income and follow Kilian's (2009) approach for constructing an index of global real economic activity.

Figure 3 depicts these macroeconomic variables, along with shaded regions that represent the presence of HPAI in U.S. poultry. The broiler meat market contributes little to these macroeconomic variables, so we treat these variables exogenously during estimation.

Vector Autoregressive (VAR) Models

A VAR modeling framework suits our panel of endogenously linked broiler meat market variables and exogenous macroeconomic variables. VAR specifications without a moving average or error correction component require the endogenous time series to be autocorrelated and stationary.[10] While visual inspection of the series shown in Figure 1 suggests autocorrelation and trend stationarity, we apply the Durbin–Watson test for autocorrelation and an augmented Dickey–Fuller (ADF) test for trend-stationarity.[11] All test results reject the null hypothesis of 0 autocorrelation

[10] Our interest in evaluating the parameters estimates of the market responses to HPAI prompts us to test for trend stationarity. Sims, Stock, and Watson (1990) note that stationarity is not necessary to the development of IRFs.

[11] A DF-GLS test for stationarity also suggests that all series are stationary except storage at the 0.05 level.

or nonstationarity at the 5% level.[12,13] Thus, the assumptions required for the implementation of a VAR approach are satisfied.

Our general VAR specification uses a natural log transformation of endogenous variables $i \in [1,..,4]$ in levels in month $t \in [1,\dots,T]$, $\ln(y_{i,t})$. This specification includes a constant for each endogenous variable, c_i; lagged observations of all endogenous variables, $y_{j,t\text{-}l}$; and an error term, $\varepsilon_{i,t}$. We also specify a vector of exogenous covariates, x_t, and a general time-trend function, $f(t)$, in equation (1). We restrict lags to be all integers between 1 and set an upper bound, L.

$$\begin{aligned}\ln(y_{i,t}) = c_i + \phi_{1,i}\mathbb{1}_{HPAI_1}(t) + \phi_{2,i}\mathbb{1}_{HPAI_2}(t) + \sum_{j=1}^{4}\sum_{l=1}^{L}\left[\alpha_{j,l}\ln\left(y_{j,t\text{-}l}\right)\right] \\ + \boldsymbol{\beta}_i \ln(\boldsymbol{x}_t) + f(t) + \varepsilon_{i,t}.\end{aligned} \tag{1}$$

We approximate trade restrictions using indicator variables for the ORW(s). These indicator variables are a binary approximation of continuous changes in trade openness due to embargoes and other trade restrictions; $\mathbb{1}_{HPAI_1}$ and $\mathbb{1}_{HPAI_2}$ capture the 2004 and 2015 outbreak responses, respectively. In the absence of a policy variable, this event study formulation captures the trade restrictions' average effect as a structural shift in the constant terms only.

Each candidate model follows the general specification shown in equation (1), with a distinct combination of indicator function(s), covariates, lags, and time trends. These regressors can take any form from a prespecified set (when included).

The pronounced stability of broiler markets supports the assumption that observations during and outside of outbreak restrictions differed only by trade openness. Only a single rapid shift is observed around the Great Recession. Furthermore, according to a Wilcoxon rank-sum test, the residuals from this model do not systematically differ between 2000–2001 and 2002–January 2004 nor between 2000–May 2007 and June 2007–November 2014.[14] Similarly, F-tests results suggest that the variance of residuals remained constant or declined for all series except prices. A VAR model explains most of the variation within this system. We find that estimating a specification like equation (1) without the dummy variables has R^2 values between 0.78 and 0.94. This stability results from the concentration of and specialization in broiler production and the fact that broiler growers typically operate under long-term contracts (MacDonald, Hoppe, and Newton, 2018).

Considered Specifications

To reduce specification uncertainty, we select an optimal model(s), M^*, from a large set of VAR models, M^0. Each candidate model represents a unique combination of outbreak response specification, dynamic trends, and selected exogenous variables. The optimal model is selected based on the Akaike information criterion (AIC) value it generates. For a comprehensive discussion of model selection, see the online supplement.

The indicator variables capture the timing of shifts in the broiler market variables in the ORW. We allow for the magnitude of the outbreak responses to be similar ($\boldsymbol{\phi}_1 = \boldsymbol{\phi}_2$) or for one or both of the outbreaks to be excluded from the specification ($\boldsymbol{\phi}_1 = 0, \boldsymbol{\phi}_2 = 0$, or $\boldsymbol{\phi}_1 = \boldsymbol{\phi}_2 = 0$). The ORW(s) can begin anytime between the August preceding each outbreak until the August following each outbreak. We confine the maximum length of each outbreak response to 15 months. While some HPAI related embargoes persisted through our time series (e.g., China), these were likely attributable to factors other than the risk from HPAI spread.

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[12] See the online supplement for a complete description of our tests for the necessary conditions for a VAR approach.

[13] A Breusch–Godfrey test applied to our preferred specification does not suggest serial correlation in the residuals.

[14] We find a statistically significant difference only between the residuals on storage between the periods 2000–2001 and 2002–January 2003.

We capture seasonality and long-run dynamics, respectively, with monthly fixed-effects and a linear trend. We also test a cubic B-spline with three knots, which leads to greater (worse) AIC values and similar estimated outbreak responses.

Candidate models may include global real economic activity, domestic per capita income, industrial energy prices, soybean meal prices, or corn prices. The interactions between the macroeconomy and months-long responses guided us to exclude lags of the exogenous variables.

We consider lag specifications that range between 0 and 12 months for the endogenous variables. Optimal lag structures were not sensitive to the maximum lag length, L; increasing the maximum lag length came at higher computational costs.

Results and Discussion

We estimate the impacts of HPAI on the U.S. broiler meat market by imposing an ORW and using model selection to identify an ORW that best fits the data. Comparisons with a naïve approach highlight the added value of model selection. Using a naïve approach leads to significantly more information loss, which indicates that our estimates are derived from a specification that is not well suited to the underlying data. For models chosen based on model selection, estimated producer welfare loss from HPAI and the ensuing embargoes are between $30 million and $137 million greater than those found using simulation techniques and more than $3 billion below those found using simple dynamic comparisons.

We complement our estimation of the market responses to HPAI by evaluating our optimal model's statistical performance. This model exhibits minor differences from the set of weak candidates, indicating only mild unresolved specification uncertainty.

The online supplement also includes several supplementary discussions. The estimates from the optimal VECM model are not qualitatively different from those found using VAR models. Impulse response functions (IRF) characterize the convergence back to equilibrium after a brief shock.

Comparison of Event Study Approaches

We evaluate the performance of three approaches in which specifications are chosen based on economic intuition, IC values, or a mixture. Our first set of estimates is derived from a model in which an event is imposed based on OIE terrestrial guidelines (World Organisation for Animal Health, 2021). All other specification choices are also imposed. We refer to this as the "naïve model." Our second set of estimates is generated by a model selection process in which the ORWs are still imposed but other specification choices are selected to minimize information loss. The best model selected from this process is referred to as the "optimal event study" (OES) model. Our third model allows for the optimal selection of all specification choices, including the timing of the ORWs. We refer to this as the "fully optimal" (FO) model.

The use of model selection markedly improves the statistical performance of the OES approach relative to the naïve model by providing a better characterization of the underlying market dynamics. The FO model performs better than the OES model and provides insights into the duration of market impacts, which are missed by the other two models.

For the naïve and OES models, we select an ORW based on when the disease was reported (January–June 2015) and OIE Terrestrial Codes, which recommend imposing embargoes for at least 4 months following an outbreak (through October 2015).[15] The naïve model (2) imposes a simple lag structure (e.g., 2 months), (2) specifies the ORW as the period during which HPAI is present in the U.S. poultry flock, (2) treats the market responses to the HPAI outbreaks with a

[15] HPAI is a "notifiable" event that must be reported to OIE immediately. There is only a brief delay between the first infection and reporting, which would not be consequential given that our data are monthly. OIE guidelines do not explicitly address how to adjust embargoes when wild hosts are infected with HPAI.

Table 1. Percentage Changes in Broiler Market Variables during Highly Pathogenic Avian Influenza Outbreaks in 2004 and 2014/15

Model	Outbreak	Exports	Prices	Storage	Production
Naïve	Feb–Jun 2004 &	-10.3^{***}	-0.2	2.3^{*}	-0.8
	Jan–Oct 2015, combined	(3.0)	(1.3)	(1.3)	(1.1)
Optimal event study	Feb–Jun 2004 &	-23.2^{***}	2.4	7.0^{***}	-2.0
		(5.3)	(2.1)	(2.2)	(1.6)
	Jan–Oct 2015, split	-5.4	-1.3	0.03	-0.5
		(3.4)	(1.3)	(1.4)	(1.0)
Fully optimal	Feb–Jun 2004 &	-23.3^{***}	2.3	7.1^{***}	-1.9
		(5.2)	(2.0)	(2.2)	(1.6)
	July–Nov 2015, split	-12.2^{***}	-3.7^{**}	3.1^{*}	-0.6
		(4.6)	(1.8)	(1.9)	(1.4)

Notes: Single, double, and triple asterisks (*,**,***) indicate signifcance at the 10%, 5%, and 1% level. Numbers in parentheses are standard deviations.

single indicator variable, (4) includes all possible covariates, and (5) imposes a specification that accounts for seasonality and long-run trends. The OES approach relaxes assumptions 1 and 3–5, and allows these features to be determined by AIC values. Our FO model selection routine relaxes the assumption about the start and end dates of the ORW (assumption 2) and instead selects the minimum AIC value from a large set of candidate response windows.

While our model selection routines largely confirmed choice 5 and partially confirmed choice 4, choices 1–3 would have led to a specification that poorly fit the data. When the ORWs are selected using AIC values, they roughly align with those that we imposed. The first outbreak perfectly aligns, while the second outbreak begins 6 months later and ends 1 month later. This alignment largely allays fears that we are detecting a different shock. Furthermore, the underlying treatment is continuous (rather than discrete), and our approach is designed to find large responses rather than estimate the effect of an observed, binary treatment. The delayed market response indicates that trade restrictions affected markets after international guidelines would have suggested.

Table 1 presents the percentage change in broiler market variables during each outbreak for each of the three models. As shown in Table 1, the coefficient estimates from all models indicate substantial export declines in response to both outbreaks.[16] For both the optimal event study and fully optimal models, the other economic responses differ between outbreaks. Both models generally agree that producers increased storage in 2004 (by 7% or 7.1%) and prices declined in 2015 (by 1.3% or 3.7%). There is no evidence of production declines in response to either outbreak.

The timing and magnitude of the decline in exports following the second outbreak align with Ramos, MacLachlan, and Melton's (2017) description and estimates. We find a smaller change in exports (-12.2% for 5 months versus -18% for 6) relative to Ramos, MacLachlan, and Melton. The decline in exports during and after the 2004 HPAI outbreak was -23.3% over 5 months. Using a t-test on the parameter values provides strong evidence ($p < 0.01$) that the export response to the 2004 outbreak was greater than the export response to the 2014–2015 outbreak in percentage terms, despite the much larger magnitude of the 2014–2015 outbreak. This result supports Thompson's (2018) finding that regionalization and other policy changes between 2004 and 2014–2015 may have dampened the trade impact of HPAI.

[16] The full set of estimated parameters for our optimal model can be found in the online supplement.

Embargoes (and other trade restrictions) typically decrease domestic prices as the pool of potential consumers shrinks. During the 2014–2015 outbreak response, we observe a 3.7% price decrease. The statistically insignificant changes in price during the 2004 outbreak may be attributable to the relatively low prices preceding this period, which resulted from other disease and sanitation concerns (Leuck, Haley, and Harvey, 2004). HPAI outbreaks in other countries may have also improved general market conditions for U.S. producers.

Increased storage occurred during both outbreak responses ($7.1\% and 3.1\%$), although the storage response to the second outbreak was only significant at the 0.1 level. Challenges in finding new consumers or expectations of improved market conditions typically motivate increased storage. The uncertainty about the duration and economic effect of the 2014–2015 outbreak may have discouraged storage. Additionally, a shift in consumers' preferences toward fresh (not frozen) chicken made storage a less desirable option in response to the 2014–2015 outbreak (Thompson, 2018). Before the 2004 outbreak, storage also represented 28.5% of production on median, while exports represented 15.9% of production. Therefore, the estimated decline in exports represented 3.7% of total production, while the increase in storage represented 2% of production. A similar comparison for the 2014–2015 outbreak suggests that the export losses represented 2.3% of total production, and the increase in storage was only 0.6%.

Neither outbreak caused significant reductions in broiler meat supply from disease-related losses. The economically small and statistically insignificant changes in broiler production suggest fixities in the production process that prevent responses to short-run changes in market conditions. The industrial nature of broiler production or contracts may make rapid adjustments to an ephemeral event less practical.

Soybean meal prices were included in the optimal model but no other input prices.[17] A 1% increases in soybean prices were associated with statistically significant increases in exports (0.17%) and decreases in storage (-0.037%). Increased soybean prices were also associated with economically small decreases in production (-0.02%) that were statistically significant at the 0.1 level. A 1% increase in global real economic activity correlates with a 0.01% decrease in storage and a 0.01% increase in production in the short run. Domestic disposable income was not included in the optimal model, indicating its limited explanatory power.

The information gain from using our optimal model is substantial. The difference in AIC estimates between the optimal and naïve models is $\Delta = 127$. As shown in Table 1, the model selected based on economic intuition measures only a smaller decline in annual exports (10.3%) and no other statistically significant changes in the broiler meat market. The occurrence of detectable changes—as indicated by the ORW chosen by our optimal model selection routine—*after* the HPAI outbreaks lead to underestimated market responses. The shortcomings of selection based on intuition highlight the value of our model selection approach.

Evaluating the outbreaks as separate events leads to a reduction in AIC of 2.9. Following the approach for statistical inference of AIC values detailed by Burnham, Anderson, and Huyvaert (2011), we find that models that pool the HPAI outbreaks are approximately 23% as likely as our optimal model to be the true model.[18]

Suboptimal Models and Remaining Specification Uncertainty

AICs provide an imperfect measure of Kullback–Leibler (1951) divergence. Following the inference of Burnham and Anderson (2004), the suboptimal models with slightly lower AIC values provide are used to describe the remaining specification uncertainty. Within $M^0 \backslash M^*$, $2 < \Delta_h$ for 14 models,

[17] The full set of parameter estimates for the optimal VAR and VECM specifications are included in the online supplement.
[18] The probability of an alternative model being the "true model" instead of the model that yields the lowest AIC is $\exp((AIC_{min} - AIC_{alternative})/2\}$.

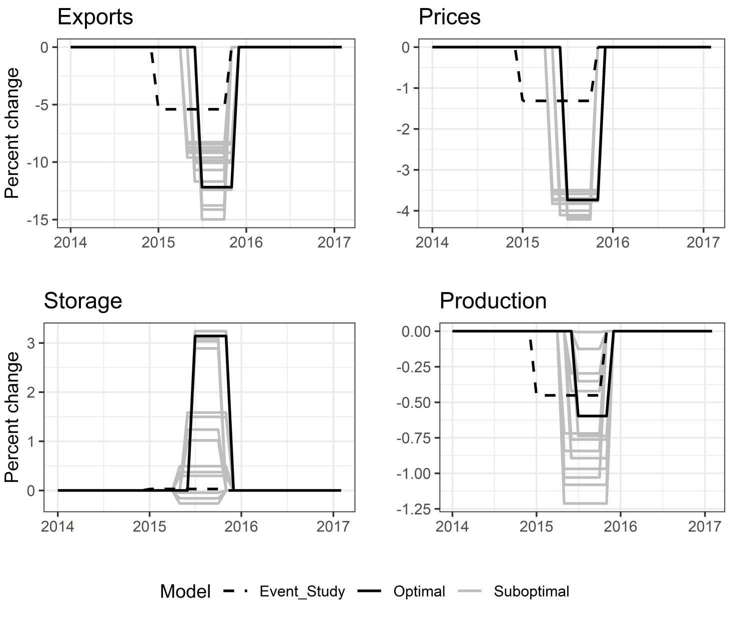

Figure 4. The Imposed, Optimal, and Suboptimal Event Windows for the Market Response to the 2014–2015 Outbreak of HPAI

indicating the possibility of other strong candidate;[19] 42 models are weak candidates, and the remaining 4,286,435 models do not merit consideration. We focus on 14 strong alternative candidates.

Figure 4 displays the timing and magnitude of outbreak responses for each of the broiler market variables. We include results for the OES ("imposed" for clarity) and FO ("optimal") models. The results from five models with slightly worse performance ($2 < \Delta_h$) than the FO model ("suboptimal") are also shown. The optimal and imposed ORWs overlap with January, February, March, April, May, June, and November 2015 lying outside of this intersection. This agreement among the specifications indicates that the effects of trade restrictions likely coincided more closely with the spike in disease prevalence than the first case of HPAI. The effect of trade restrictions on markets lasted approximately as long as expected.

The suboptimal models indicate the robustness of this ORW. These candidate models all have outbreak responses within the range of the optimal model (July–November 2015). The optimal and suboptimal specifications include monthly fixed effects and global economic activity. The suboptimal models included either a linear trend or per capita income. Similarly, these models included either soybean meal or corn prices, indicating that only one of these variables provided unique information. Each has an optimal lag length of 4 months.

Welfare Comparison

The decrease in the aggregate broiler meat price illuminates the economic impact of HPAI on broiler producers. The limited response of broiler production to HPAI suggests that the percentage change in prices would approximately equal the percentage change in revenues. A lack of information on changes in the cost of broiler meat production limits our welfare comparison to using revenues to approximate producer surplus.

[19] Most statistical software packages select the number of lags and whether to include a constant, and we do not consider these specifications separately. We treat the 4,286,435 combinations of ORWs and covariates as unique.

The 3.7% price decrease between July and November 2015 translates to an approximately 1.5% decrease in annual revenues. Average annual revenues between 2010 and 2014 were over \$30.3 billion, translating to approximately \$472 million in lost revenues in 2015.[20] Among the strong alternative candidate models, the range of revenue losses ranged from \$418 million to \$635 million. An estimated \$332 million revenue decline is found using the price change and ORW for the OES, while the naïve approach leads to an approximate \$51 million decline.

Our market response estimates exceed the \$276 million in welfare losses estimated by Johansson, Preston, and Seitzinger (2016)[21] and are substantially lower than the \$4 billion year-over-year change in nominal broiler producer revenue reported by Ramos, Maclachlan, and Melton (2017). Lower simulated production may have reduced Johansson, Preston, and Seitzinger's estimate of net losses, while the relatively high broiler meat prices immediately before the outbreak may have elevated Ramos, MacLachlan, and Melton's year-over-year estimates. The changes in feed prices described by Johansson, Preston, and Seitzinger were not detectable in the data. While feed prices decreased between 2014 and 2015, these prices continued to decline through the end of our time series (Figure 3). Our approach to identifying the observed broiler meat market response to HPAI improves on these previous studies by applying time-series techniques; including additional data; and accounting for market dynamics, trends, and macroeconomic conditions.

Conclusions

The market responses to infectious disease outbreaks and ensuing trade restrictions can be considerable but are often difficult to measure due to a lack of publicly available data on the timing and form of these restrictions and uncertainty about how importers respond to changes in risk in the absence of embargoes. Interactions with external macroeconomic factors, long-run trends, and the rigidity of production introduce additional challenges. Economists have primarily relied on simulations and basic statistics to infer losses. Simulations rely heavily on the modeler's understanding of the system, and basic statistics may be sensitive to short-term fluctuations. Our econometric approach improves upon the methods used in previous studies (e.g., Greene, 2015; Johansson, Preston, and Seitzinger, 2016; Ramos, Maclachlan, and Melton, 2017). We empirically measure—rather than impose—different economic responses between outbreaks, mild production responsiveness to economic conditions, and the value of regionalization. Our estimates could be used to simulate changes within markets more precisely, which improves the measurement of benefits from disease eradication policies for the agricultural economy. An improved understanding of these benefits subsequently informs the evaluation of alternative disease mitigation policies.

Our estimates suggest that trade restrictions had substantial effects on aggregate U.S. broiler meat exports (-23.3% in 2004 and -12.2% in 2015). The smaller percentage change in exports occurred even though HPAI was present in 15 states and had infected wild hosts during the 2014–2015 outbreak. The adoption of OIE guidelines on regionalization by foreign importers was likely behind the reduced effect of embargoes and is supported by the findings in previous literature (Johnson et al., 2015; Thompson, 2018). Our estimates help quantify the impacts of trade restrictions and provide information that could be used to identify the value of mitigation options (e.g., prenegotiated regionalization agreements).

Few broiler chickens were lost in either outbreak, and statistically significant production effects were not observed. However, distinct economic responses accompanied the export declines between the two outbreaks. In response to the 2004 HPAI outbreak, producers significantly increased storage (7.1%). The rapid response for disease eradication, the presence of HPAI in other broiler producing countries, and low broiler meat prices before the outbreak increased incentives to divert meat to cold storage. This result may support closer consideration of cold storage management by government

[20] Annual revenues were adjusted for inflation to 2019 dollars.
[21] \$295 million in 2019 dollars.

animal health authorities and industry, while trade embargoes are imposed due to animal health events.

In contrast, the 2014–2015 outbreak led to lower prices (-3.7%) and smaller short-run storage increases (3.1%). The approximately 6-month duration of the outbreak and the uncertainty about prevalence likely contributed to price declines. Regionalization combined with little to no avoidance of poultry meat by U.S. consumers in this period motivated a lower percentage increase in cold storage compared to the 2004 HPAI event. Consumers' growing preference for fresh meat may have also influenced producers' storage decisions (Thompson, 2018).

Our findings support the observation of Ramos, Maclachlan, and Melton (2017) that production declines in response to the HPAI outbreak were mild. The results presented in this paper indicate producers' insensitivity to short-term changes in economic conditions. Although the two outbreaks were quite different in magnitude and length, which made comparing them difficult, the results better quantify the benefits of disease eradication to the U.S. poultry sector. To fully quantify the benefits of HPAI eradication, the possible benefit to human health and the broader economy may need to be considered. Future analyses could use these results to compare against various response strategies for HPAI and could be replicated for other types of animal health events. These results help quantify the benefits of preparedness policies like regionalization agreements, particularly with close trading partners such as Canada; infrastructure for cold storage; and investments for rapid disease eradication.

[First submitted April 2020; accepted for publication March 2021.]

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Journal of Agricultural and Resource Economics 47(1):S1–S7 ISSN 1068-5502

doi: 10.22004/ag.econ.310527

Online Supplement: Market Responses to Export Restrictions from Highly Pathogenic Avian Influenza Outbreaks

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Autocorrelation, Stationarity, and Cointegration

We test for autocorrelation and trend-stationarity among our broiler meat market variables. These features support the use of VAR models without transformation, although stationarity may not be necessary to apply a VAR framework (Sims, Stock, and Watson, 1990). We test for autocorrelation using the Durbin-Watson test for autocorrelation of disturbances, using a threshold of 0.05. Table A1 shows the probability that disturbances are uncorrelated over time. We find compelling evidence that these data are indeed autocorrelated over time.

Table S1. *P*-Value from Durbin-Watson Test for Autocorrelation

Exports	Prices	Storage	Production
<0.01	<0.01	<0.01	<0.01

An Augmented Dickey-Fuller (ADF) approach is used to test for trend-stationary. In Table A2, we report the *p*-values associated with these test statistics. The results of the ADF test provide strong evidence that the data are trend-stationary (or tend to revert to a linear trend over time).

Table S2. *P*-Value from Dickey-Fuller Test for Stationarity

Exports	Prices	Storage	Production
0.038	0.032	0.044	<0.01

The presence of non-stationarity and cointegration in related time-series indicates that a VECM (rather than VAR) approach should be used. As indicated by the results of our ADF tests in the previous subsection, however, our data are trend-stationary. A VECM is, therefore, unnecessary but may still help to characterize the behavior of the market far from equilibrium.

A Johansen's test for cointegration allows us to determine if our time-series are cointegrated and at what rank. Our Johansen's test of the four endogenous variables indicates that these series have a cointegration rank of 3 at a 5% confidence level. We, therefore, proceed with the VECM as an alternative to the VAR.

For each candidate VECM model, we determine the cointegration rank while accounting for the structural breaks, covariates, and trends. An optimal model with a cointegration rank of zero or 4 (full rank) would suggest that a VAR approach should replace the VECM approach.

Model Selection

When the underlying data generating process is unknown, results depend on the assumptions the researcher uses in selecting a specification. Economists traditionally appealed to theory or previous research when selecting covariates, specifying lag structures, and characterizing endogeneity. More recently, economists have applied more rigorous model selection criteria to address specification uncertainty, particularly when selecting a lag structure. These approaches select lag lengths based on model fit—as defined by the maximized value of the likelihood function—and impose a penalty for the number of parameters used, avoiding problems associated with overfitting (Keuzenkamp and McAleer, 1995). Our model selection approaches determined the optimal specification of lag length, time-trend, and the set of included exogenous variables. We also extend these principles to address specification uncertainty about the timing of the market responses to the HPAI outbreaks. For one of our model selection approaches, the periods when the dummy variables ($\mathbb{1}_{HPAI}$) change from 0 to 1 and 1 to 0 (the ORWs) are selected based on their ability to explain the data.

As noted in Carter and Smith (2007), an event study that uses a structural break test may not allow for causal interpretation in the presence of other events that exacerbate or mitigate changes in the variables of interest. The break dates may also not accurately reflect the treatment window, and the average treatment effect estimates will be biased. The confounding events noted in the *International Trade Policy Response* section could introduce bias, although the direction of this bias is unclear, and the magnitude is likely small. We, therefore, also estimate a model where the dates used in $\mathbb{1}_{HPAI}$ are imposed. While this approach cannot correct for the bias introduced into the ϕ parameters by omitted events, it does provide results from a plausible response window and an example for comparison.

The distance between the true data generating process and a statistical model can be described using Kullback-Leibler (KL) divergence, which could be estimated using a variety of ICs (Kullback and Leibler, 1951). Because our core goal is to tease out the broiler meat market's responses to past HPAI outbreaks, we choose to use the Akaike information criterion (AIC) as a measure of KL divergence instead of the Bayesian information criterion (BIC), which typically characterizes model performance in forecasting (Akaike, 1974 and Engle and Brown, 1986).

ICs share the general characteristic that they favor models with a better fit while penalizing models with more parameters. The AIC (along with other ICs such as the BIC) balance the negative log-likelihood function (as a measure of model fit) with the number of parameters included. The AIC is generally defined as

$$AIC = 2p - 2\ln\left(\Lambda\left(\boldsymbol{y};\hat{\boldsymbol{\theta}}\right)\right), \tag{S1}$$

where p denotes the number of parameters and $\Lambda\left(\boldsymbol{y};\hat{\boldsymbol{\theta}}\right)$ represents the likelihood function evaluated at the optimal (maximizing) parameters, $\hat{\boldsymbol{\theta}}$. The negative log-likelihood function in equation 2 captures the goodness of fit across alternative ICs, and $2p$ is a penalty for the number of included parameters.[1]

Using the notation presented by Hansen, Lunde, and Nason (2011), we define the optimal model or set of models, M^*, from the set of candidate models, M^0 indexed $h \in [1,\dots,H]$. We then characterize a distance or loss function between any two models as the difference in their AIC values: $\mu_{i,j} = E\left(d_{i,j}\right) = AIC_i - AIC_j$. A model is considered optimal if its AIC score is equivalent to the minimum AIC for all models:[2]

$$M^* \equiv \left\{i \in M^0 : \mu_{i,j} \leq 0\ \forall\ j \in M^0\right\}. \tag{S2}$$

Note that an AIC value provides only an estimate of KL divergence and the optimality of M^* is therefore uncertain. The true optimal model could lie in the complement of M^*, $M^0 \backslash M^*$. Furthermore, we specify many models with only small differences, which could lead to statistically

[1] The BIC follows a similar specification except that the parameter penalty function is $\ln(n)\,p$, where n denotes the number of observations. Because $\ln(n) > 2$ whenever $n > 7$, the use of BIC typically favors more parsimonious models. These more parsimonious models may perform better in forecasting.

[2] Note that we find the optimal lag length, $\hat{L}_h$, within $\hat{\boldsymbol{\theta}}_h$, and that the value of $\hat{L}_h$ determines the number of excluded observations in each model.

Table S3. Percent Changes in Broiler Market Variables during Highly Pathogenic Avian Influenza Outbreaks in 2004 and 2014/15—Fully Optimal VECM Model

Outbreak	Exports	Prices	Storage	Production
2004	-19.4^{***}	3.0	6.5^{**}	−1.4
	(5.0)	(2.0)	(2.1)	(1.6)
2014/15	-11.2^{*}	-4.7^{**}	1.1	−0.8
	(4.1)	(1.6)	(1.7)	(1.3)

Notes: Single, double, and triple asterisks (*,**,***) indicate signifcance at the 10%, 5%, and 1% level. Standard deviations are shown within parentheses.

insignificant differences between AIC values. Hansen, Lunde, and Nason (2011) develop a theory for rigorous consideration of a small set of suboptimal models given the uncertainty regarding KL divergence estimation, which has been implemented for forecasting techniques (for an example in R, see Bernardi and Catania, 2018). To consider how well our model explains past events (and not how well it predicts future events), we instead employ the AIC inference techniques suggested by Burnham and Anderson (2004), who define $\Delta_h = AIC\left(\hat{\boldsymbol{\theta}}_h\right) - AIC\left(\tilde{\boldsymbol{\theta}}\right) \leq 0$. Models with $\Delta_h \leq 2$ should be strongly considered, those with $4 \leq \Delta_h \leq 7$ are weak candidates, and those with $10 < \Delta_h$ are not worth considering.

Vector Error Correction Models

In addition to VAR models, we consider a Vector Error Correction Models (VECM), which may better explain changes in the system's behavior away from equilibrium. While our ADF test results suggest that the data are trend-stationary and error correction is unnecessary, we explore this specification as a plausible alternative to a VAR.[3] Standard VECM approaches typically first difference the data, which is also an available modification to our VAR models.[4] The error correction approach includes additional terms that return a system to equilibrium more quickly when the system is farther from equilibrium. Mathematically, this amounts to first differencing each endogenous and exogenous variable, and adding an error correction term (ECT), $\Pi \ln(Y_{t-1})$.

(S3) $$\Delta \ln(y_{i,t}) = c_i + \phi_{1,i}\mathbb{1}_{HPAI_1}(t) + \phi_{2,i}\mathbb{1}_{HPAI_2}(t) + \Pi \ln(Y_{t-1})$$

To implement this approach, the rank of integration, r, must be determined, which we find using the Johansen procedure (Johansen, 1988). The ECT is assigned dimension $4\ x\ r$.[5]

The trend-stationarity of our data does not support the inclusion of error correction terms, at the 0.05 level. If we instead imposed a stricter standard to reject the null hypothesis of a unit root (e.g., 0.01), then we would proceed with a series of VECM models. Applying a Johansen test for cointegration, we find that the data are cointegrated.

The optimal VECM model estimates market responses similar to the VAR approach, while many of the core characteristics are identical (number of lags, time-trends, and monthly fixed effects). The VECM model includes corn prices while it omits soybean prices and real economic activity. The ORW timing is modeled as May thought October, which is slightly earlier than the optimal model for the VAR approach. The optimal model has a cointegration rank of one.

Table A3 displays the same parameter estimates from Table 1 that addresses the fully optimal model selection approach, but for the VECM specification.

The optimal response found for the 2004 outbreak is identical to that found using the VAR approach. The parameter estimates for this outbreak are also very close in magnitude. The modeled

[3] If the data were non-stationary, cointegration tests would suggest the use of VECM specification over a VAR. See the Appendix for more detail.
[4] Because our data is already trend-stationary, we opt not to also take the first difference.
[5] ECT terms are generally assigned dimensions $k\ x\ r$, where k is the number of equations (or endogenous variables).

Table S4. Full Set of Parameter Estimates from the Optimal VAR Specification (N = 224)

	Endogenous variables			
	Exports	**Prices**	**Storage**	**Production**
2004 event	−0.233***	0.023	0.071***	−0.019
	(0.052)	(0.02)	(0.022)	(0.016)
2014/15 event	−0.122***	−0.037**	0.031*	−0.01
	(0.046)	(0.018)	(0.019)	(0.014)
Exports L.1	0.241***	−0.01	0.0003	−0.028
	(0.074)	(0.029)	(0.031)	(0.022)
Price L.1	0.024	1.181***	−0.096	−0.123**
	(0.184)	(0.072)	(0.076)	(0.055)
Storage L.1	0.274	−0.074	1.005***	0.066
	(0.172)	(0.067)	(0.071)	(0.052)
Production L.1	0.281	−0.027	0.366***	−0.291***
	(0.242)	(0.095)	(0.100)	(0.073)
Exports L.2	0.017	−0.0001	0.021	−0.028
	(0.074)	(0.095)	(0.1)	(0.073)
Price L.2	0.142	−0.401***	0.264**	0.136
	(0.277)	(0.108)	(0.115)	(0.083)
Storage L.2	−0.015	0.111	−0.211**	−0.72
	(0.239)	(0.094)	(0.115)	(0.072)
Production L.2	−0.316	−0.074	0.146*	0.136**
	(0.194)	(0.076)	(0.080)	(0.058)
Exports L.3	0.146**	0.055*	−0.009	−0.018
	(0.073)	(0.028)	(0.030)	(0.022)
Price L.3	−0.188	−0.106	−0.139	0.084
	(0.277)	(0.108)	(0.115)	(0.083)
Storage L.3	−0.23	−0.187	0.364***	0.032
	(0.237)	(0.093)	(0.098)	(0.071)
Production L.3	−0.038	0.059**	0.11	0.662***
	(0.192)	(0.075)	(0.079)	(0.058)
Exports L.4	0.074	−0.053	0.03	0.025
	(0.067)	(0.026)	(0.028)	(0.02)
Price L.4	0.145	0.152**	0.007	−0.081
	(0.179)	(0.070)	(0.074)	(0.054)
Storage L.4	0.18	0.088	−0.279***	−0.057
	(0.17)	(0.067)	(0.071)	(0.051)
Production L.4	−0.589**	0.045	−0.267***	0.064
	(0.236)	(0.092)	(0.098)	(0.071)
Soybean meal price	−0.170***	0.02	−0.037**	−0.02*
	(0.039)	(0.015)	(0.016)	(0.012)
Economic activity	0.011	0.001	−0.009	0.012***
	(0.013)	(0.005)	(0.005)	(0.004)
R2	0.801	0.926	0.922	0.939
Adjusted R2	0.768	0.913	0.909	0.929
Residual SE	0.091	0.036	0.038	0.027
F stat (df=32; 191)	24.1***	74.5***	70.9***	91.5***

Notes: Single, double, and triple asterisks (*,**,***) indicate signifcance at the 10%, 5%, and 1% level. Standard deviations are shown within parentheses.

Table S5. Full Set of Parameter Estimates from the Optimal VECM Specification (N = 223)

	Endogenous variables			
	Exports	**Prices**	**Storage**	**Production**
2004 event	−0.194***	0.03	0.065**	−0.014
	(0.052)	(0.02)	(0.022)	(0.016)
2014/15 event	−0.112**	−0.047**	0.011	−0.075
	(0.041)	(0.016)	(0.017)	(0.013)
Exports L.1	−0.345***	−0.01	−0.052	0.008
	(0.095)	(0.037)	(0.04)	(0.029)
Price L.1	0.003	0.274***	−0.085	−0.124*
	(0.186)	(0.072)	(0.077)	(0.058)
Storage L.1	0.195	−0.11	0.04	0.063
	(0.182)	(0.071)	(0.076)	(0.056)
Production L.1	−0.096	0.001	0.374***	−1.206***
	(0.258)	(0.101)	(0.108)	(0.08)
Exports L.2	−0.344***	−0.011	−0.044	−0.024
	(0.092)	(0.036)	(0.039)	(0.029)
Price L.2	0.011	−0.125	0.165*	0.013
	(0.187)	(0.073)	(0.078)	(0.058)
Storage L.2	0.187	0.037	−0.13	−0.03
	(0.168)	(0.066)	(0.07)	(0.052)
Production L.2	−0.362	−0.012	0.579***	−0.913
	(0.393)	(0.153)	(0.164)	(0.122)
Exports L.3	−0.166	0.053	−0.066	−0.035
	(0.084)	(0.033)	(0.035)	(0.026)
Price L.3	−0.108	−0.206**	−0.008	0.104
	(0.186)	(0.73)	(0.078)	(0.058)
Storage L.3	−0.11	−0.157*	0.24***	0.011
	(0.168)	(0.066)	(0.07)	(0.052)
Production L.3	−0.066	0.072	0.615***	−0.112
	(0.384)	(0.15)	(0.16)	(0.12)
Exports L.4	−0.121	0.008	−0.033	−0.001
	(0.068)	(0.027)	(0.029)	(0.021)
Price L.4	0.151	−0.126	0.131	0.022
	(0.182)	(0.071)	(0.076)	(0.057)
Storage L.4	0.201	−0.001	−0.226*	−0.023
	(0.172)	(0.067)	(0.072)	(0.054)
Production L.4	−0.303	0.058	−0.226*	−0.023
	(0.249)	(0.097)	(0.104)	(0.077)
Corn price	−0.042*	0.006	0.004	−0.001
	(0.019)	(0.008)	(0.008)	(0.003)

Notes: Single, double, and triple asterisks (*,**,***) indicate signifcance at the 10%, 5%, and 1% level. Standard deviations are shown within parentheses.

timing of the ORW does not significantly affect the parameter estimates. The VECM specification leads to smaller monthly changes in exports and larger changes in prices during the 2015 ORW.

Complete Estimation Results for the Fully Optimal Model

In addition to the parameters of interest, we estimate parameters that describe the relationships between the endogenous variables and lags of all endogenous variables, $\boldsymbol{\alpha}$ time trends $f(t)$, and

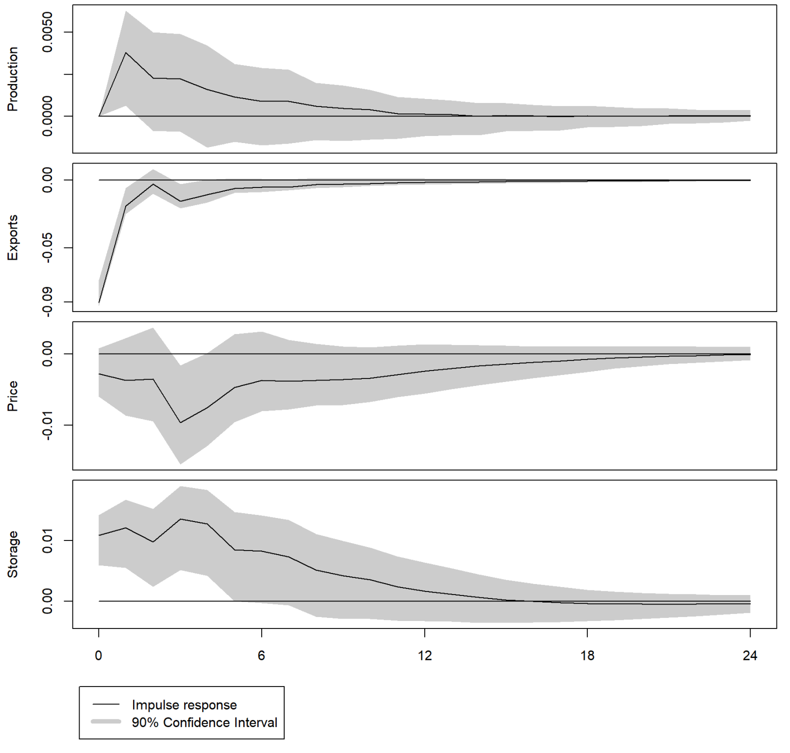

Figure S1. The Response of Endogenous Broiler Meat Market Variables to a One Standard Deviation Decrease in Exports

exogenous variables, $\boldsymbol{\beta}$. These parameters allow for a better identification of $\boldsymbol{\phi}$, and the IRFs depend on our estimates of $\boldsymbol{\alpha}$. We present the full set of parameters for the optimal VAR model in Table A4 and the optimal VECM model in Table A5.[6]

Impulse Response Functions and Long-Run Dynamics

Our specification in equation 1 models the average market response to HPAI outbreaks but does not explicitly characterize the convergence to equilibrium after an outbreak. Orthogonal impulse response functions (IRF), often seen in the related literature, use the optimal parameter estimates, $\hat{\boldsymbol{a}}$, to characterize a typical market response to an external change in one of the endogenous variables. This article focuses on measuring the size and timing of market responses to disease outbreaks, and our IRF is intended only to provide insight into long-run convergence and an example of how the parameter estimates from this article could be used elsewhere.

Estimation of IRFs typically relies on theoretical reasoning to select a functional form that captures the effect of an exogenous shock on a market variable, which then results in changes in other endogenously linked variables. For livestock markets measured at monthly intervals; however, a definite theory about the appropriate functional form does not exist. We identify the IRF from our VAR results using a recursive ordering approach with the following order of variables: production, exports, prices, and storage. The rigidity of the broiler production system led us to place it first. We placed exports second because international trade volumes often depend on political relationships beyond the domestic broiler meat market. This placement also reflects our interest in market

[6] The tables represent the unadjusted parameter values. We can convert the parameters in this table to those represented in Table 1 by multiplying each parameter by 100.

responses to trade restrictions. The ordering of prices and storage was arbitrary but did not affect our results.

In Figure A1, we show impulse responses to a one standard deviation decline in exports (approximately 10%) and the corresponding 90% confidence interval.[7] This decline conveniently aligns with the export declines from the 2014/15 outbreak of HPAI.

Exports initially converge quickly, but the export decline persists at a very low level for 15 months. Much like in the months following the 2014/15 outbreak, the IRFs model a period of high storage for months following a negative export shock. We estimate that changes in prices or production are not statistically significant following export shocks. The statistically insignificant change in prices reflects the broiler meat market's average response to a brief shock to exports, and may not characterize particular events or persistent shocks (for example, the 2014/15 outbreak response) well.

[7] 1,000 bootstrapped runs were used to develop the confidence interval.